Evaluation of a wireless low-energy mote with fuzzy algorithms and neural networks for remote environmental monitoring

Ricardo Yauri, Jinmi Lezama, Milton Rios
National Institute of Telecommunications Research and Training-National University of Engineering, Perú

Article Info	ABSTRACT
	The devices developed for applications in the internet of things have evolved technologically in the improvement of hardware and software components, in the area of optimization of the life time and to increase the capacity to save energy. This paper shows the development of a fuzzy logic algorithm and a power propagation neural network algorithm in a wireless mote (IoT end device). The fuzzy algorithm changes the transmission frequency according to the battery voltage and solar cell voltage. Moreover, the implementation of algorithms based on neural networks, implied a challenge in the evaluation and study of the energy commitment for the implementation of the algorithm, memory space optimization and low energy consumption.

Corresponding Author:

Ricardo Yauri
National Institute of Telecommunications Research and Training (INICTEL-UNI)
National University of Engineering (UNI)
National University of San Marcos (UNMSM)
1771 San Luis Avenue, Lima, Perú
Email: ryauri@inictel-uni.edu.pe, ryaurir@unmsm.edu.pe

1. INTRODUCTION

Smart IoT devices are currently generating new applications in the area of the internet of things (IoT) as part of a System that will provide users with an information monitoring service [1]. Different authors describe hardware and software techniques to improve node uptime [2], [3]. The simulation of fuzzy algorithms in parallel allows to improve the control and use of the energy so that the IoT devices can operate for longer, modifying the idle time and the transmission power. This is described in [4] where it is shown that 25% efficiency can be achieved with respect to a common implementation. The work developed in [5] shows a proposal for a system based on fuzzy logic algorithms using the MATLAB platform, always focusing on the programming and optimization of these models in devices with low hardware and energy resources. The use of neural networks and their application in embedded systems with low hardware resources and power limitations (also considering ubiquity and wireless transmission) is not inconvenient for implementing this type of algorithms in devices closer to the data source [6]-[8]. As a result, the machine learning (ML) models and associated ML inference framework must not only run efficiently, but must also operate in a few kilobytes of memory [9]-[11].

With the above, it can be understood that adding a block of intelligence using inference algorithms, the IoT nodes can reduce their energy consumption [12]. Furthermore, it is understood that the problems of an adequate implementation of algorithms in a sensor node [13] (neural networks or fuzzy algorithms) can be reduced by comparing the energy consumption during communication and the energy used to execute the

algorithms. This aspect takes on an important relevance when wireless sensor nodes are used in monitoring environments where they need to function continuously, ubiquitously and unattended for long periods of time.

With revisions made in this paper, algorithmic techniques shown to reduce power consumption hardware systems that need to send information with variable frequencies without affecting the behavior of the IoT node [14]. This paper contributes to the study of the feedpropagation neural network algorithm (and the calculation of the centroid (fuzzy algorithm) for its implementation in a sensor node with limited hardware resources [15], being a novel aspect its comparative evaluation for its use in environmental monitoring applications [16], [17]. In this way, we show the evaluation of a wireless sensor node with fuzzy and neural network algorithm for remote environmental monitoring.

2. RESEARCH METHOD

This section shows the design and implementation of a Mandami fuzzy algorithm and a feedpropagation neural network [18], [19]. The input data for the algorithms will be the battery and solar cell voltage, which will modify the transmission period and allow the evaluation of the lifetime, the rate of transmitted packets and their relation to energy consumption. Three sensor nodes are implemented, two of them with the inference models and the other with a constant transmission period to perform the evaluations of the results under the same conditions. The sensor nodes transmit their information to a web server using a communication interface based on ZigBee technology.

2.1. Control system to optimize energy consumption using diffuse algorithms

A Fuzzy model will be developed, which takes as inputs the battery voltage and solar cell voltage and varies the transmission frequency of the IoT node. The Mamdani model is presented in Figure 1, in order to generate an output that will vary the transmission periods [20].
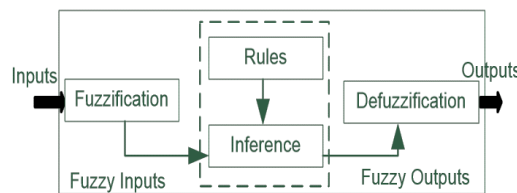

Figure 1. Structure of a fuzzy logic system

2.2.1. Inputs of the proposed system

According to the background check, it was found that the voltage of the battery and solar cell affect the operating time of the IoT device, for which they were chosen as inputs to the fuzzy algorithm. Table 1 and Table 2 show the inputs the membership functions with linguistic values. For each variable, 3 ranges of values were defined using two types of function (triangular, trapezoid) in the bottom, middle and upper ranges in order to calculate the centroid and obtain the value of the transmission time.

Table 1. Membership function: battery voltage

Input		limit values [V]		
variable	Type	Bottom	Middle	Top
μ_{batt_low}	Trapezoid		$a_1 = 3.5$	$a_2 = 3.8$
μ_{batt_med}	Triangular	$b_1 = 3.6$	$b_2 = 3.85$	$b_3 = 4.1$
μ_{batt_high}	Trapezoid	$c_1 = 3.9$	$c_2 = 4.2$	

Table 2. Membership function: solar panel

Input		limit values [V]		
μ_{cell_low}	Trapezoidal		$d_1 = 3.3$	$d_2 = 3.5$
μ_{cell_med}	Triangular	$e_1 = 2.4$	$e_2 = 4.0$	$e_3 = 5.6$
μ_{cell_high}	Trapezoidal	$f_1 = 4.5$	$f_2 = 4.0$	
μ_{cell_low}	Trapezoidal		$d_1 = 3.3$	$d_2 = 3.5$

2.1.2. Output variable

The frequency or period of transmission is considered as the fuzzy output variable, having three possible values: "fast shipping time [tfast]", "average send time [tavg]" and "slow sending time [tslow]".

2.2. Embedded neural network for energy optimization

The model based on neural networks shown in Figure 2, consists of 4 fundamental elements: input neurons with scaling, operations on the neurons of the hidden layers together with the weights and pathways, and the output layer, where the activation function indicate the type of output to be obtained. The system with the neural network model implements techniques based on the feedforward process due to the limited hardware resources of the embedded system [21] whose algorithms have been adapted to optimize memory

space as described in some research [22], [23]. The model assigns specific values for the output labels, as shown in Table 3, the output values as shown in Table 4, are composed of four neurons that will be activated independently, using the sigmoid function, within a multiclass classification system. Figure 3 shows the methods and functions implemented for the execution of the neural network algorithm considering the hidden layer, the output layer and the activation functions. With the above considerations, the implementation of a neural network architecture based on the scheme shown in Figure 4 with 2 input neurons, 1 hidden layer with 3 neurons and 4 neurons in the output layer.
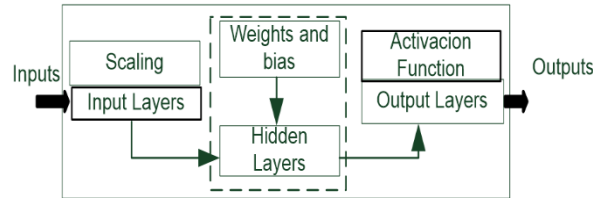

Figure 2. Scheme of feedforward neural network

Table 3. Relationship levels with values for classification

	Id label	voltage	Value label
Battery	$\mu_{batt\_low\_nn}$	3.4	-1
	$\mu_{batt\_med\_nn}$	3.8	0
	$\mu_{batt\_high\_nn}$	4.3	1
Solar panel	$\mu_{cell\_low\_nn}$	2	-1
	$\mu_{cell\_med\_nn}$	4	0
	$\mu_{cell\_high\_nn}$	6	1

Table 4. Neural network output values

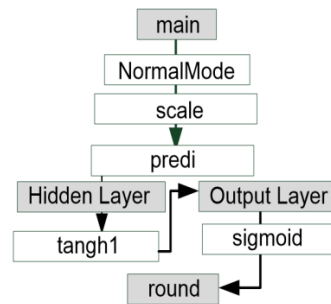|	Id label	Time transmission	Output values			
			O1	O2	O3	O4
Output	T_{n1}	10	1	0	0	0
	T_{n2}	20	0	1	0	0
	T_{n3}	30	0	0	1	0
	T_{n4}	40	0	0	0	1

Figure 3. Programming functions used in the neural network algorithm
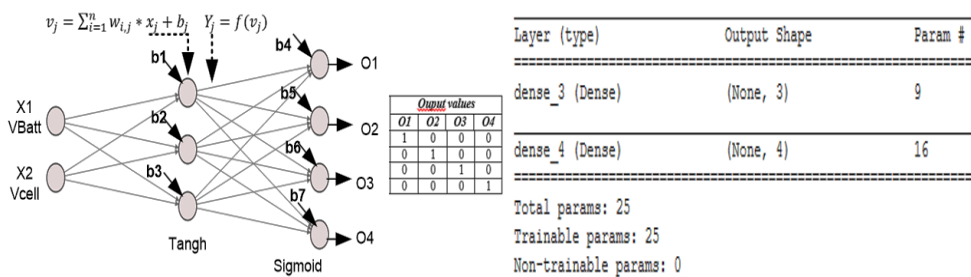

Figure 4. Feedforward network execution process and resulting model

2.3. Implementation

The evaluation of the techniques to modify the data submission period in the MATLAB simulation software was carried out at the beginning of the study. Then the algorithms were validated, implementing them in C language for an embedded system. The function of the fuzzy algorithm is the task of Fuzifying the inputs (µbatt and µcell) using membership functions. As a second stage, the rules are evaluated with the antecedent and consequent values calculated in each rule as shown in Table 5.

Table5. Fuzzy association matrix

Voltage		Panel Solar [V]		
		μ_{cell_low}	μ_{cell_med}	μ_{cell_high}
Battery	μ_{batt_low}	t_{slow}	t_{slow}	T_{avg}
	μ_{batt_med}	t_{slow}	T_{avg}	T_{avg}
	μ_{batt_high}	T_{avg}	T_{fast}	T_{fast}

In the case of the model that implements the feedforward neural network, the relationship between the input voltage values and the transmission time period is observed in Table 6. With this relationship, the network is trained and validated using the libraries of TensorFlow, keras and the python programming language in the JupyterLab development environment [24], [25]. The structure of main functions that the neural network implements is shown in Figure 3. In Figure 4 we observe the variables used to calculate the output in the network, considering the bias and weights.

Table 6. Neural network association matrix

Voltage		Panel Solar [V]		
		$\mu_{cell\_low\_nn}$	$\mu_{cell\_med\_nn}$	$\mu_{cell\_high\_nn}$
Battery	$\mu_{batt\_low\_nn}$	Tn4	T_{n4}	T_{n3}
	$\mu_{batt\_med\_nn}$	T_{n3}	T_{n3}	T_{n2}
	$\mu_{batt\_high\_nn}$	T_{n3}	T_{n2}	T_{n1}

3.   RESULTS AND DISCUSSION
3.1. Sensor node and transmission period control

Three wireless sensor nodes were implemented as shown in Figure 5, in order to evaluate their behavior in the hardware. The Node, called "M1", was programmed with the fuzzy method, the Node "M2" with a time of 20 seconds and the Node "M3" programmed with the neural network algorithm. The wireless nodes "M1", "M2" and "M3" perform the acquisition of sensor data to validate their operation in environmental monitoring environments. For them it was necessary to acquire information on the humidity level and ambient temperature. In Figure 6, the variation of the transmission times during the first 4 load cycles is shown for sensor node "M2", when evaluating the input parameters in the neural network, which is updated when executing the feedforward neural network, which has a direct impact on energy consumption. Table 7 presents the execution times of each sensor node process. With these results it is verified that the execution time of the fuzzy technique (11 milliseconds) does not negatively affect the operation time of the sensor node.
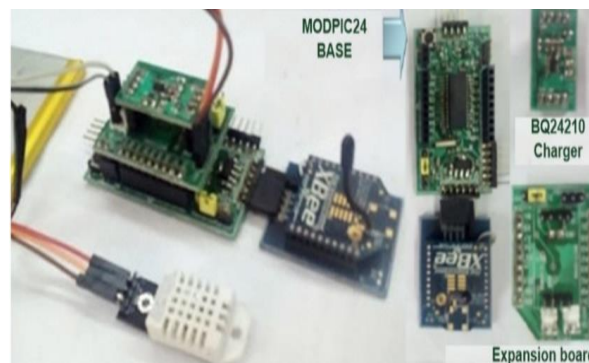

Figure 5. Assembled sensor node (left) and its components (right)

The increase in the transmission periods, the number of transmitted bytes increases in node "M1", as seen in Figure 7. This happens at the beginning of the operation process, obtaining more information without negatively affecting the node's energy consumption. The data of the transmission period change process are shown in Table 8, observing that the longest duration of the M3 node, with the neural network algorithm, reaches up to 63 days. Furthermore, the node "M3", the transmission periods are kept in a constant range of values (unlike the fuzzy algorithm) obtaining a lower number of bytes sent as shown in Table 9.
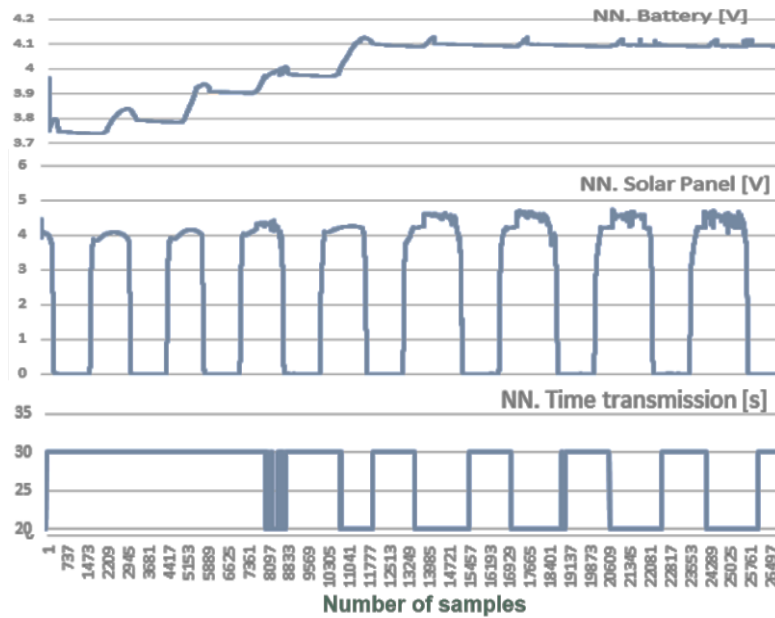

Figure 6. Battery and solar cell voltage according to the transmission period for the neural network at node "M2"

Table 7. Process duration efficiency

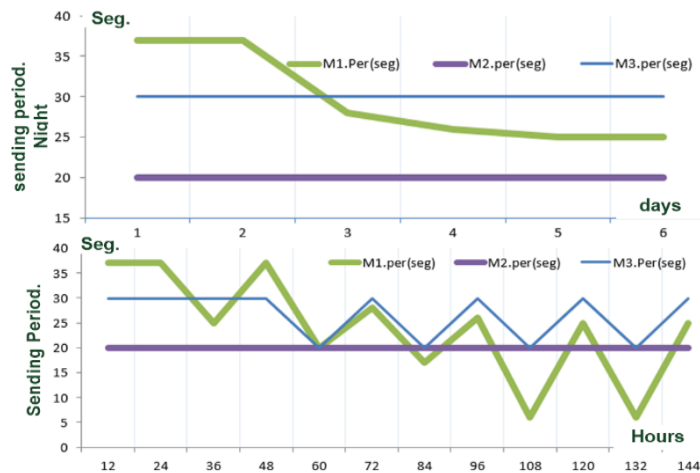| n	Processes	M1 [ms]	M2 [ms]	M3 [ms]
1	Start message	19	19	19
2	Data processing	1140	1140	1140
3	Data sending time calculation (M1 only)	11	3	4
4	Data transmission (serial port)	157	157	157
	Total	1327	1319	1320

Figure 7. Battery and solar cell voltage according to the transmission period for the neural network model and fuzzy model

Table 8. Days of operation of nodes M1, M2 and M3

		M1		M2		M3	
	Day number	Time [s]	Duration [days]	Time [s]	Duration [days]	Time [s]	Duration [days]
Day	1	36	71	20	47	30	63
Night		37	71	20	47	30	63
Day	2	24	55	20	47	30	63
Night		37	72	20	47	30	63
Day	3	21	47	20	47	20	47
Night		28	60	20	47	30	63
Day	4	17	40	20	47	20	47
Night		26	57	20	47	30	63
Day	5	5	17	20	47	20	47
Night		24	55	20	47	30	63
Day	6	6	16	20	47	20	47
Night		24	56	20	47	30	63

Table 9. Bytes sent in the period of 6 days (144 hours)

		Accumulated bytes		
Number	Hours	M1	M2	M3
0	0	58	58	58
1	12	100224	125280	83520
2	24	167943	250560	167040
3	36	268167	375840	250560
4	48	335886	501120	334080
5	60	461166	626400	459360
6	72	550652	751680	542880
7	84	698040	876960	668160
8	96	790840	1002240	751680
9	108	1041400	1127520	876960
10	120	1141624	1252800	960480
11	132	1559224	1378080	1085760
12	144	1659448	1503360	1169280

Figure 8 shows that node "M1" exceeds the amount of information sent by node "M2" since the fifth day. Also, similarly, during the 4 days "M1" exceeds "M3" in the amount of information sent. This is because the solar panel and the battery of the node "M1" have a suitable voltage value, to reduce the transmission period at night.
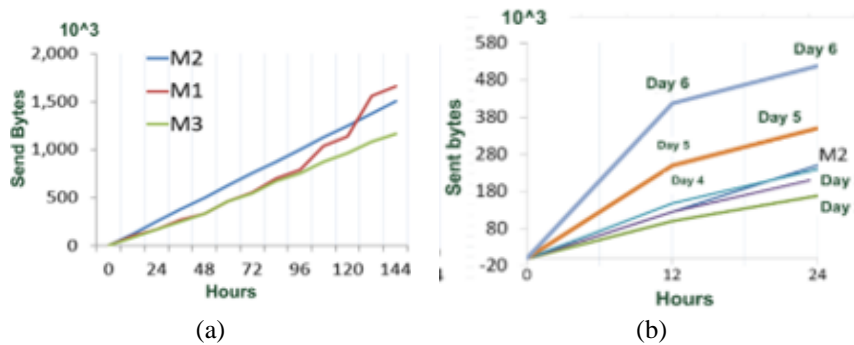

Figure 8. These figures are; (a) bytes accumulated and (b) sent each day

3.2. Neural network implemented

Table 10 shows the size of each type of algorithm to be implemented in an embedded system and the number of functions used for its deployment. During the tests, the classification process was verified, using the model trained and validated on a computer, and the model implemented in the sensor node M3 with the algorithm implemented in C language.

Table 10. Features models

	Functions numbers	Size file (KBytes)	Algorithm/Model
Fuzzy Algorithm	7	7.93	Mandami (centroid)
Neural Network	5	3.88	Feed Propagation

4. CONCLUSION

Process execution duration of the fuzzy algorithms, where it is observed that these are 3 times greater than the behavior of a node in normal mode (M2), but even so it does not negatively alter energy consumption. In the case of node M3, the increase in the execution time of the neural network model is 33% compared to M1. In addition, node M1 is always the one that consumes more execution time compared to M2 and M3, in addition to sending more data packets it sends. In summary, the neural network in M3 can last longer than node M1, transmitting less data and making the same decisions.

The fuzzy algorithms increase the useful life by approximately 50% compared to the node in normal operation, this evaluation being carried out daily independently. When the evaluation is made considering the evolution of the duration trend of node M1, it has less autonomy of operation than node "M2". The number of bytes sent to node "M1" increased by 30% compared to node "M2", noting that this does not negatively affect the operation duration of the node. In the case of node M3, during the first days it is surpassed in daily autonomy by M1, but when the review of the accumulated trend is carried out, node M3 exceeds the autonomy time of M1 by 22% and the M2 by 12%. The evaluation carried out brought as a benefit the importance of files size used for the implementation of the algorithms, where the neural network model is about 50% smaller compared to the fuzzy inference model, for which is the most suitable in terms of optimization the memory space consumption. The neural network model consumes less time in its processes, being almost at the same level as an embedded one without any processing algorithm (M2). The advantage of implementing inference models in sensor nodes allows them to make decisions to save energy based on their knowledge of their environment, behaving like cognitive devices. As future work, decision-making and transmission time evaluation could be optimized by considering a more continuous output range by migrating the model to the regression type. The article has limitations on the parameters used for decision making, because it did not consider environmental sensors as an important factor. Furthermore, only a specific type of fuzzy algorithm and neural network was evaluated.

REFERENCES

[1] S. I. D. Guerrero, J. A. C. Carrero, and O. A. C. G omez, "Analysis of the Fog and Edge Computing Paradigm in Spain: Análisis del Paradigma Fog y Edge Computing," *Universidad Industrial de Sandander Bucaramanga*, Bucaramanga, Colombia 2018.

[2] K. A. Kumar and K. Jayaraman, "Irrigation control system-data gathering in WSN using IOT," *International Journal of Communication Systems,* vol. 33, no. 16, 2020, doi: 10.1002/dac.4563.

[3] S. Venkataramani, K. Roy, and A. Raghunathan, "Efficient embedded learning for IoT devices," *2016 21st Asia and South Pacific Design Automation Conference (ASP-DAC)*, 2016, pp. 308-311, doi: 10.1109/ASPDAC.2016.7428029.

[4] M. Collotta, G. Scatà, S. Tirrito, R. Ferrero, and M. Rebaudengo, "A parallel fuzzy scheme to improve power consumption management in Wireless Sensor Networks," *Proceedings of the 2014 IEEE Emerging Technology and Factory Automation (ETFA)*, 2014, pp. 1-4, doi: 10.1109/ETFA.2014.7005363.

[5] J. Zhang, J. Chen, and Y. Sun, "Transmission power adjustment of wireless sensor networks using fuzzy control algorithm," *Wireless Communications and Mobile Computing,* vol. 9, no. 6, pp. 805-818, 2009, doi: 10.1002/wcm.630.

[6] O. B. Tariq and M. T. Lazarescu, "Neural Networks for Indoor Person Tracking With Infrared Sensors," *IEEE Sensors Letters,* vol. 5, no. 1, pp. 1-4, 2021, doi: 10.1109/LSENS.2021.3049706.

[7] C. De la Parra and A. Guntoro, "Improving approximate neural networks for perception tasks through specialized optimization," *Future Generation Computer Systems,* vol. 113, no. 597-606, 2020, doi: 10.1016/j.future.2020.07.031.

[8] P. Warden and D. Situnayake, "Tinyml: Machine learning with tensorflow lite on arduino and ultra-low-power microcontrollers," O'Reilly Media, 2020.

[9] F. Shahid and A. Zameer, "A novel wavenets long short term memory paradigm for wind power prediction," *Applied Energy,* vol. 269, 2020, doi: 10.1016/j.apenergy.2020.115098.

[10] S. K. Malchi and S. Kallam, "A trust-based fuzzy neural network for smart data fusion in internet of things," *Computers & Electrical Engineering,* p. 89, 2021, doi: 10.1016/j.compeleceng.2020.106901.

[11] J. Wang, "An intelligent data gathering schema with data fusion supported for mobile sink in wireless sensor networks," *International Journal of Distributed Sensor Networks,* vol. 15, no. 3, 2019, doi: 10.1177%2F1550147719839581.

[12] R. Yauri, J. Lezama, and M. Rios, "Wireless Low-Energy mote Based on Fuzzy Algorithms for Environments Quality Monitoring Applications," de *2020 IEEE Engineering International Research Conference*, Lima, 2020, doi: 10.1109/EIRCON51178.2020.9254073.

[13] D. K. Jana and S. Basu, "Novel Internet of Things (IoT) for controlling indoor temperature via Gaussian type-2 fuzzy logic," *International Journal of Modelling and Simulation,* pp. 1-9, 2019, doi: 10.1080/02286203.2019.1682420.

[14] G. Crocioni, "Li-Ion Batteries Parameter Estimation With Tiny Neural Networks Embedded on Intelligent IoT Microcontrollers," *IEEE Access,* vol. 8, 2020, doi: 10.1109/ACCESS.2020.3007046.

[15] Z. H. Wang and G. J. Horng, "A vehicle safety monitoring system based on the Internet of things and the identification of physiological characteristics," *Computers & Electrical Engineering,* vol. 89, 2021, doi: 10.1016/j.compeleceng.2020.106946.

[16] N. Abdullah, *et al.*, "Towards Smart Agriculture Monitoring Using Fuzzy Systems," in *IEEE Access*, vol. 9, pp. 4097-4111, 2021, doi: 10.1109/ACCESS.2020.3041597.

[17] S. Ghorpade, M. Zennaro, and B. S. Chaudhari, "Towards green computing: intelligent bio-inspired agent for IoT-enabled wireless sensor networks," *International Journal of Sensor Networks,* vol. 35, no. 2, pp. 121-131, 2021, doi: 10.1504/IJSNET.2021.113632.

[18] K. B. Cabé and G. Xou, *Simple MLP - NeuralNetwork Library For Microcontrollers*, GitHub, 2021. [Online]. Available: https://github.com/GiorgosXou/NeuralNetworks

[19] A. Jafari, A. Ganesan, C. S. K. Thalisetty, V. Sivasubramanian, T. Oates, and T. Mohsenin, "SensorNet: A Scalable and Low-Power Deep Convolutional Neural Network for Multimodal Data Classification," in *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 66, no. 1, pp. 274-287, Jan. 2019, doi: 10.1109/TCSI.2018.2848647.

[20] G G. Chiesa, D. D. Vita, A. Ghadirzadeh, A. Hernando, M. Herrera, and J. C. L. Rodriguez, "A fuzzy-logic IoT lighting and shading control system for smart buildings," *Automation in Construction,* vol. 120, 2020, doi: 10.1016/j.autcon.2020.103397.

[21] A. Kumar, V. Seshadri, and R. Sharma, "Shiftry: RNN inference in 2KB of RAM," *Proceedings of the ACM on Programming Languages,* no. 182, pp. 1-30, 2020, doi: 10.1145/3428250.

[22] G. Lavanya, C. Rani, and P. Ganeshkumar, "An automated low cost IoT based Fertilizer Intimation System for smart agriculture," *Sustainable Computing: Informatics and Systems,* vol. 28, 2020, doi: 10.1016/j.suscom.2019.01.002.

[23] T. Tsai and C. Hsu, "Implementation of Fall Detection System Based on 3D Skeleton for Deep Learning Technique," in *IEEE Access*, vol. 7, pp. 153049-153059, 2019, doi: 10.1109/ACCESS.2019.2947518.

[24] R. David, *et al.*, "Tensorflow lite micro: Embedded machine learning on tinyml systems," *arXiv preprint arXiv:2010.08678,* 2020.

[25] A. Géron, *Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*, USA: O'Reilly Media, 2019.

BIOGRAPHIES OF AUTHORS

Ricardo Yauri is a Master of Science in Electronic Engineering with a Mention in Biomedical. He has participated as a teacher in courses oriented to the Internet of things and applications in home automation and the Cisco academy for IoT. Currently, he is a researcher at INICTEL-UNI in the Embedded Systems and Internet of Things research group. He is an associate professor at the Universidad Nacional Mayor de San Marcos (UNMSM).

Milton Rios is a graduate of the Universidad Nacional Mayor de San Marcos, has a professional degree in Electronic Engineering, with a Master's degree in Telecommunications at the Ricardo Palma Private University, currently he works as a research professional at the National Institute of Training and Research in Telecommunications of the National University of Engineering (INICTEL-UNI), he is also a professor at the Faculty of Electronic and Electrical Engineering of the UNMSM.

Jinmi Lezama is a Doctor in Electronic Systems from the University of Lorraine - France, a Master in Embedded Electronic Systems and microelectronics from the Henri Poincaré University - France. Engineer from the National University of San Antonio Abad del Cusco, Peru. He worked as a researcher in the research group "Embedded Systems and Communications" in the Directorate of Research and Technological Development DIDT of INICTEL-UNI and the National University of Engineering. He currently works as a research professor at the Technological University of Lima Sur (UNTELS)